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Machine Learning Techniques for Personalized Detection of Epileptic Events in Clinical Video Recordings

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Abstract *Continuous patient monitoring is essential to achieve an effective and optimal patient treatment in the intensive care unit. In the specific case of epilepsy it is the only way to achieve a correct diagnosis and a subsequent optimal medication plan if possible. In addition to automatic vital sign monitoring, epilepsy patients need manual monitoring by trained personnel, a task that is very difficult to be performed continuously for each patient. Moreover, epileptic manifestations are highly personalized even within the same type of epilepsy. In this work we assess two machine learning methods, dictionary learning and an autoencoder based on long short-term memory (LSTM) cells, on the task of personalized epileptic event detection in videos, with a set of features that were specifically developed with an emphasis on high motion sensitivity. According to the strengths of each method we have selected different types of epilepsy, one with convulsive behaviour and one with very subtle motion. The results on five clinical patients show a highly promising ability of both methods to detect the epileptic events as anomalies deviating from the stable/normal patient status.*

Introduction

Epilepsy is one of the most common disorders of the brain with a global number of 45.9 million patients with all-active epilepsy (both idiopathic and secondary epilepsy) and an age-standardised prevalence of 6.2 per 1000 population[1]. Manifestations of epilepsy are epileptic seizures, recurrent paroxysmal events characterised by stereotypical behavioural alterations reflecting the neural mechanisms involved in the epileptic process[2]. Diagnosis of this disorder is a challenging task, which relies on the experience of the attending physician in assessing both the Electroencephalogram and the clinical image during and in-between seizures. Misdiagnosis of epilepsy reaches a rate of 30%[3] and has tremendous consequences on the quality of life of the wrongly diagnosed patient, experiencing side effects of medication, unnecessary driving restrictions and serious employment problems[4]. Moreover, the semiology of epileptic seizures differs from patient to patient, even within the same type of epilepsy. As a result, the motion patterns associated to an epileptic manifestation are very specific to each individual and creating a generalized model that fits all epilepsies is highly challenging. A personalized approach in assessing epilepsy is a promising solution towards effective automated patient monitoring. In this work we assess two machine learning methods, dictionary learning (well established) and an LSTM autoencoder (SoA), to automatically detect epileptic events in a personalized manner. We perform this on clinical video recordings of patients in two different settings, during long-term video-EEG monitoring in a specialized epilepsy centre and during clinical monitoring in the neuro-intensive care unit of a university hospital. Continuous patient monitoring in both cases is essential to detect signs of state deterioration or imminent complications. We focus on automatic video monitoring to bridge the gap between continuous automatic vital sign monitoring and manual, costly, monitoring from specially trained and highly experienced personnel.

Realted Work

A systematic review of methods in vision-based analysis of epileptic seizures differentiates between marker-based and marker-free techniques[5]. Marker-based systems require visibly distinctive markers (e.g. IR reflective patches) to be physically attached to the human body. These markers are then tracked with simple image segmentation techniques. Marker-free methods, initially used techniques such as optical-flow and frame differencing[6] for feature extraction and support vector machines or “shallow” artificial neuronal networks for detection and classification. Marker-based systems are usually more precise in capturing human motion but require a costly and space demanding laboratory setup. Therefore, much attention has been currently set on developing marker-free systems that benefit from the latest advances in image capturing technologies and machine learning, offering much more flexibility considering the video acquisition setup and detection capabilities. A 3D video-EEG analysis system based on color and depth cameras (RGB-D) was recently developed for the quantification of motion in epileptic seizures. A correlation of 84.2% to a marker-based approach was found and this solution has been integrated into an epileptic monitoring unit, allowing for 24/7 patient monitoring[7]. Motion quantification is performed with optical flow and further enhanced with the information form the depth image. Furthermore, deep learning methods have been employed in facial expression analysis of 2D videos of patients with mesial temporal lobe epilepsy (MTLE) by comparing traditional facial landmark features with features derived from a pre-trained convolutional neuronal network (CNN) in combination with a long short-term memory (LSTM) network[8]. This CNN/LSTM approach was further expanded with a CNN human pose estimator within a fusion strategy to differentiate between patients with MTLE and patients with extratemporal lobe epilepsy (ETLE)[9]. Finally, hand detection was introduced, resulting in a hierarchical multimodal system that to detect and quantify semiologic signs of MTLE and ETLE[10].

Methods

The main idea behind this work is to treat epileptic seizure detection as a personalized data anomaly detection problem. This is performed by evaluating the reconstruction error of a model that is trained to reconstruct input data that is known to belong to the normal/stable class only. The higher the reconstruction error of any new test instance, the further away it is from the normal class. To effectively model the known data we use two different techniques for two different types of epilepsies.

a) For seizures with distinct convolutional manifestations we employ dictionary learning, a method that is commonly used in anomaly detection tasks[11,12] and is very efficient in encoding the most important aspects of data without the need of heavy computational power. The motion patterns in this group cover large distances (10–30 cm) and are repetitive. This can be effectively modeled by this approach with relatively few training data since differences in the input data will be high.

b) For the subtle clinical manifestation of status epilepticus we use a much more powerful but also computationally intensive method, an autoencoder based on LSTM units. Deep autoencoders such as this have been used e.g. in computer network intruder detection[13], a common anomaly detection task. Motion distances in this type of epilepsy are very small and smooth, therefore data over several minutes of time is needed for a model to be able to learn the difference. LSTMs have been selected for this work because they are able to learn long-term dependencies by connecting previous information with the current one, as a result of their chain like architecture[14]. They have also been successfully used for action recognition[15,16], speech recognition[17] and language translation[18,19].

For both approaches we first extract meaningful features from the video. This step serves first for data anonymization, and second, for providing a more compact and descriptive representation of the important information in the video to the machine learning models. An example of the video recording scene for both cases is given in Figures 1 and 2. This study has been approved by the ethical committee of the University Hospital Zurich under Basec-Nr. 2017-01177.

Feature Extraction and Data Encoding

The most important feature of epileptic seizures is related to body motion. Therefore, we chose to use a method that is very sensitive to motion. It is based on a modified implementation of the well known space-time interest points (STIPs) introduced in 2003 by Laptev and Lindberg[20], which have been widely used in human activity recognition[21]. In order to achieve motion sensitivity, only the temporal dimension of STIPs is taken into account in our work, while the two spatial dimensions are removed from the calculation. We call these points "time interest points" (TIPs) because they are located at points where the pixel intensities change in time. For more details on the original STIPs please refer to Laptev et al.[20,22].

The detection of the TIPs is performed as follows. First the scale-space representation is applied only on the temporal domain by convolution of the input sequence f with a Gaussian kernel g with temporal variance τ_l^2 as shown in (1).

Figure 1: Example video recording scene of patient P01, diagnosed with temporal lobe epilepsy, with focal and secondary generalizing tonic-clonic seizures, as recorded at the Swiss Epilepsy Center.

Figure 2: Example video recording scene of patient P04, diagnosed with status epilepticus, as recorded at the Neurocritical Care Unit, University Hospital Zurich.

$$L(x,y,t;\tau_l^2) = g(t;\tau_l^2) * f(x,y,t)\ . \tag{1}$$

Only the temporal component is kept from the spatio-temporal second-moment matrix, which is averaged using a Gaussian weighting function shown in (2). In (2) τ_i^2 can be seen as a local scale according to $\tau_i^2 = s\tau_l^2$ and L_t^2 is the second order partial derivative of L as defined in (3).

$$\mu = g(t;\tau_i^2) * L_t^2 \tag{2}$$

$$L_t^2(x,y,t;\tau_l^2) = \partial_t^2 L \tag{3}$$

Finally, time-interest points are detected by searching for local maxima in L_t^2. In contrast to Laptev[22] it is not necessary to compute the Harris matrix. The local maxima are being found within 3 consecutive frames and thresholded ($l_{th} >= 0.001$) to return the position of the time-interest points.

To describe the image content at each TIP, the histogram-of-oriented-gradients (HOG) descriptors are used. Each local point is described by 9 HOGs taken from a 3×3 square grid of patches with a predefined size. The number of TIPs found in one frame can vary a lot. This requires the encoding of the "TIP-HOG" descriptors from each frame into a feature vector of fixed size. Therefore, the descriptors are encoded using histogram encoding. A maximum number of 1 million randomly sampled descriptors from each subject is clustered into 1000 clusters using k-Means clustering. All TIP-HOG descriptors from each frame are then hard encoded into a 1000-bin histogram.

More recently, dense trajectories have been shown to outperform STIPs in activity recognition[23]. In this work we chose to use STIPs as a basis for the motion features because they allowed an easy conversion for extracting temporal information only. Moreover, while trying to set weight on the machine learning aspect, we wanted to use more general features instead of features engineered for a specific task. Finally, some issues related to trajectory drift have been reported[23].

In order to make sure that the TIP-HOG features perform well on their own, we compared them to the well established STIP-HOG features using the KTH dataset[24] in the same manner as described by Wang et al.[21]. The KTH dataset is one of the first and most often used benchmark video datasets for activity recognition. It was split according to the original experimental setup[24]. The average accuracy using STIP-HOG descriptors reported by Wang et al. was 80.9%[21]. The authors used 4-bin HOG descriptors extracted from a 3D grid of $3 \times 3 \times 2$ cubes, multiple spatial and temporal dimensions and 4000 clusters for histogram encoding. Our experiments with TIP-HOG features achieved a higher average accuracy, namely 85.8%, with only one temporal dimension, a 2D 3×3 patch grid and 1000-bin histogram encoding. As in the work of Wang et al.[21] we also used an SVM classifier with a χ^2 kernel.

Dictionary Learning on Convulsive Epileptic Seizures

In dictionary learning we aim to learn an overcomplete basis $D \in \mathbb{R}^{d \times K}$, called a dictionary, made of K atoms being column vectors of length d. The dictionary D is learned to represent accurately a set of features Y using a linear combination X of its atoms, where only few coefficients are non-zero. The problem can be formulated as:

$$\{D, X\} = min\left\|Y - DX\right\|_F^2 \quad s.t. \quad \forall i, \left\|x_i\right\|_0 \leq s \tag{4}$$

where $\left\|\cdot\right\|_F$ is the Frobenius norm (or $L_{2,2}$ norm) of a matrix, and s the maximum number of non-zero coefficients in x_i. The dictionary D allows representing each feature vector y_i using a sparse combination of its atoms d_k ($k = 1, \ldots, K$) and x_i the vector of sparse coefficients, multiplying the dictionary atoms. The overcompleteness of such dictionary ($K >> d$) has shown to provide efficient sparse coding specific to the patterns of the features.

Dictionary learning can be used for anomaly detection if a dictionary is trained only on the data of the normal state, which the dictionary represents very specifically. During testing it will be able to reconstruct a normal state without any error but the reconstruction error of an anomaly will be high.

Herein we analyzed video data from two patients (P01 and P02) at the Swiss Epilepsy Center, Zurich. One patient diagnosed with temporal lobe epilepsy, with focal and secondary generalizing tonic-clonic seizures, and one with partially focal (right arm), sometimes secondary generalizing to tonic-clonic patterns. Both patients were diagnosed during long-term video-EEG recordings. An individual dictionary was trained for each patient using the period prior and after one epileptic event (approx. 3 minutes). The dictionary was trained using the code available from Rubinstein et al.[25] who implemented one of the most popular methods for dictionary learning, the K-SVD algorithm, in an efficient manner. As inputs, we used the encoded TIP-HOG features mentioned above. One sample represents a window of 2 seconds. Due to the low amount of data for P01 (only one epileptic event in the available video) we used $2/3$ of the normal period for training and $1/3$ for testing. For P02 we could use 80% for training and 20% for testing. From the abnormal period 100% was used for testing for all patients. All instances were randomly shuffled before being split.

Figures 3 and 4 show how the model reacts in terms of its reconstruction error during testing of the normal status that has been used for training (TRAIN), during testing of the "unseen" normal status (TEST) and testing of "unseen" epileptic event (EVENT). The high reconstruction error (rLSE) on the latter indicates an epileptic event in the video. It is evident that a simple threshold (grey horizontal line) on the reconstruction error can distinguish between a seizure and normal patient status.

LSTM Autoencoder on Subtle Manifestations of Status Epilepticus

An autoencoder is a deep neural network architecture that is trained such that the predicted output is the same as the input (unity function). It consists of an encoder network and a decoder network (Figure 5). The encoder is trained to produce an internal representation of the input in a much lower dimensionality than the original data. Based on this "latent representation", the decoder is trained to produce its output.

The model used in this work is closely described by Srivastava et al.[26] and uses Recurrent Neural Networks (RNNs) made of LSTM units for both the encoder and decoder (Figure 6). The input to the model is a sequence of feature

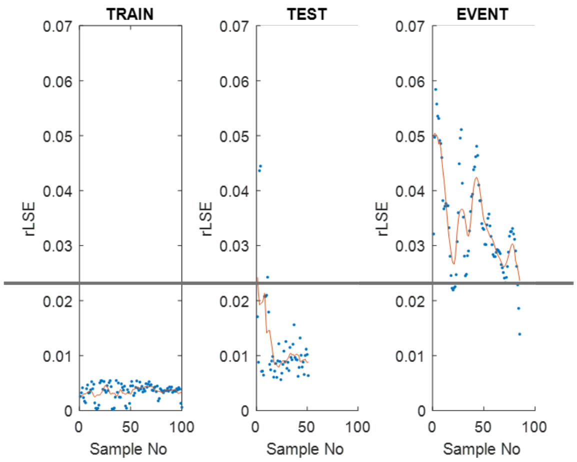

Figure 3: Patient P01, diagnosed with temporal lobe epilepsy with focal and secondary generalizing tonic-clonic seizures; Dictionary learning reconstruction error of normal patient status that has been used for training (TRAIN), of the “unseen” normal status (TEST) and of “unseen” epileptic event (EVENT).

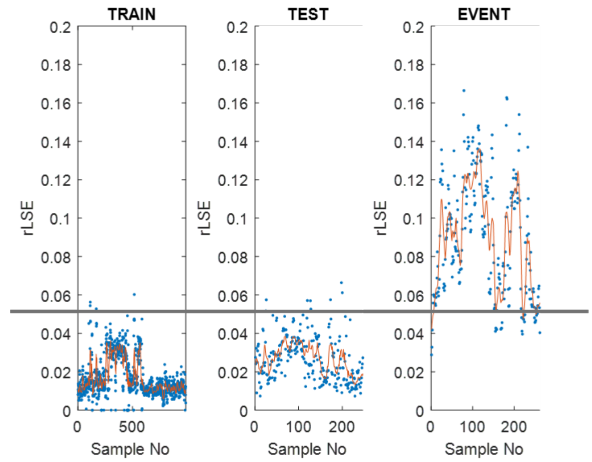

Figure 4: Patient P02, diagnosed with partially focal (right arm), sometimes secondary generalizing to tonic-clonic patterns; Dictionary learning reconstruction error of normal patient status that has been used for training (TRAIN), of the “unseen” normal status (TEST) and of “unseen” epileptic event (EVENT).

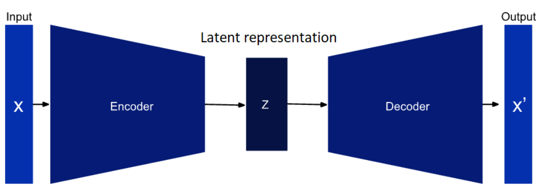

Figure 5: Schematic representation of the autoencoder.

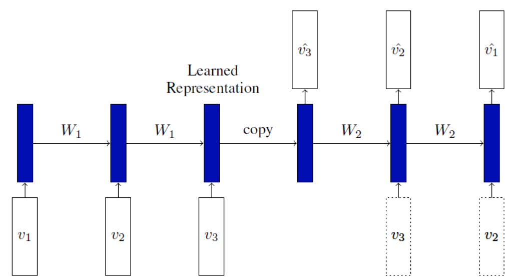

Figure 6: The LSTM autoencoder employed in this study. Image taken from Srivastava et al.[26]

vectors (TIP-HOG features), which the LSTM encoder reads in. After the last input has been read, the LSTM decoder takes over and outputs a prediction for the target sequence. The target sequence is equal to the input sequence, but in reverse order. Reversing the target sequence makes the optimization easier because the model can initiate the learning process by looking at low range correlations.

The autoencoder was trained individually on three status epilepticus patients (P03, P04 and P05) recorded at the Neurocritical Care Unit, University Hospital Zurich. Status epilepticus is a condition resulting either from the failure of the mechanisms responsible for seizure termination or from the initiation of mechanisms, which lead to abnormally, prolonged seizures. It is a condition, which can have long-term consequences, including neuronal death, neuronal injury, and alteration of neuronal networks, depending on the type and duration of seizures[27].

The annotation was performed based on EEG and video recordings. We selected the periods corresponding to the label ”status broken” as normal, these are the periods without abnormal, excessive neuronal activity. This also includes sedation patterns. Periods corresponding to labels ”status epilepticus” and ”epileptic seizure” were selected as abnormal. The video was encoded using TIP-HOG features as in the dictionary learning approach. For all patients 80% of the normal period was used for training and 20% was used for testing. From the abnormal period 100% was used for testing.

Figures 7, 8, 9 show how the autoencoder performed on the three patients. The pink/red line represents the reconstruction error for the abnormal state, while the blue/green one represents the reconstruction error for the normal state. Figures 7, 8 for patients P03 and P04 present well the difference between the normal and the abnormal states. The pink/red graph is clearly above the blue. It is important to notice that for patient P03 the duration of the normal state was excessively longer than the abnormal, while for patient P04 the opposite holds. Considering patient P05 (Figure 9, we do not observe a visible difference. In this case the patient suffered from non-convulsive status epilepticus and didn't exhibit visible movement patterns during an epileptic seizure.

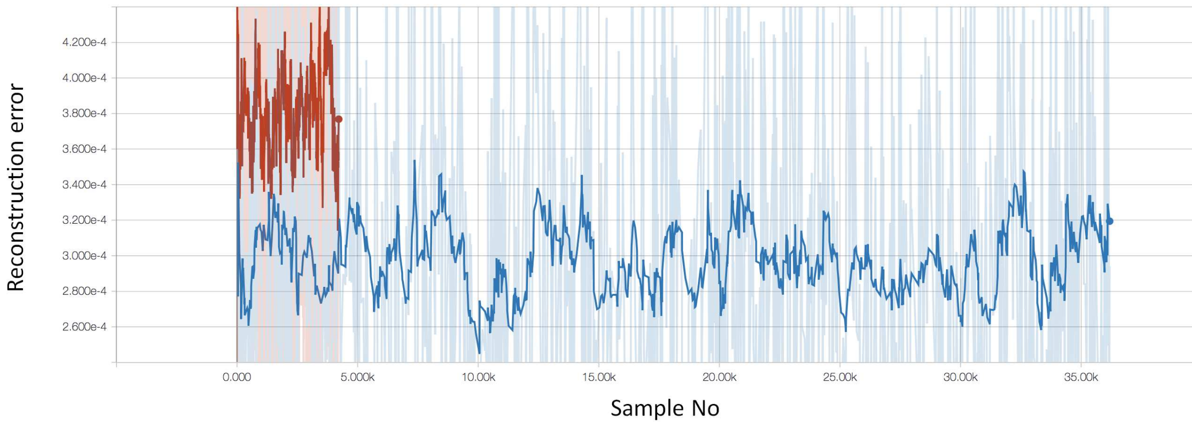

Figure 7: Patient P03, diagnosed with status epilepticus; LSTM autoencoder reconstruction error (moving average) of normal (blue) and abnormal states (red).

Figure 8: Patient P04, diagnosed with status epilepticus; LSTM autoencoder reconstruction error (moving average) of normal (blue) and abnormal states (pink).

Conclusion

In this work we have presented the application of two different machine learning methods on personalized epileptic event detection in videos. Each method has been applied on a different type of epilepsy according to its suitability. The results on five clinical patients show a highly promising ability of both methods to detect the epileptic events as an anomaly deviating from the stable/normal patient status. In one case this was not possible, a case of nonconvulsive status epilepticus, where almost no motion was visible in the video. This behavior is expected since the input features were designed with motion sensitivity in mind.

The strengths of dictionary learning lie within its low computational requirements for being trained (less than an hour

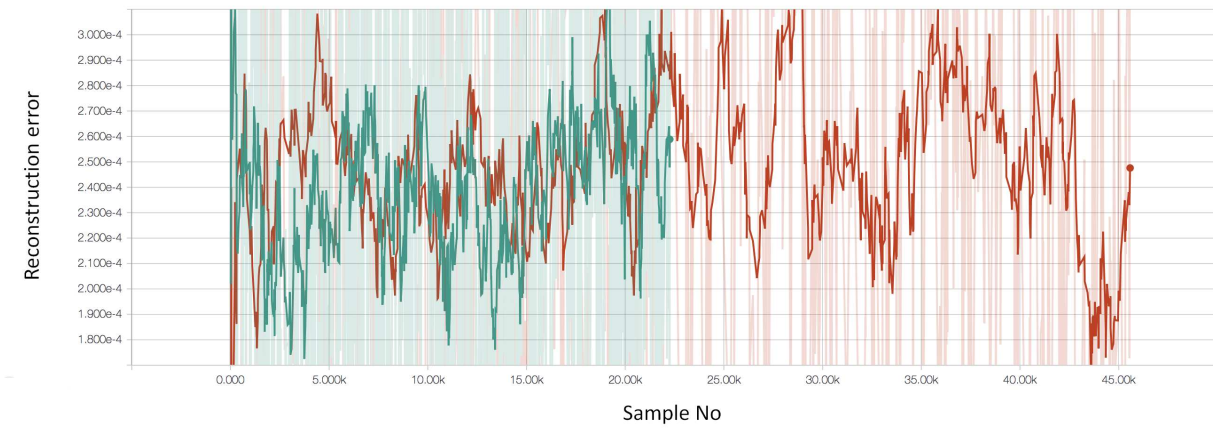

Figure 9: Patient P05, diagnosed with nonconvulsive status epilepticus; LSTM autoencoder reconstruction error (moving average) of normal (green) and abnormal states (red).

on a CPU), especially if the features used are describing the variability in the data well. Since it does not need much data to be trained it is suitable for short-term patient monitoring scenarios.

The strengths of the LSTM autoencoder are shown in its ability to process and learn more sublte epileptic manifestations on the cost of higher computational (multiple hours on a GPU) and data requirements to be trained. Being in the domain of deep learning it offers to be combined with e.g. a CNN for the extraction of features related to appearance that will help in nonconvulsive cases, a research area, which still remains open.

Both methods support online learning, this means that the more data of the stable state is becoming available while a patient is being monitored the more sensitive the model becomes against anomalies. In case an anomaly is detected it can be further classified as an epileptic seizure or another critical event, e.g. a patient falling out of the bed, with a much higher specificity. For both methods, annotation of the training data must be free of any abnormal event, since this will introduce noise in the trained model. In this case dictionary learning shows an advantage by not needing much data to be trained. This makes it easier and less time-consuming for the clinicians to annotate the video.

In the future we aim to perform the evaluation of the methods presented in this article on more patients and on longer periods of video for each. This will help us to provide a more quantitative analysis of the detecting capabilities of both methods.

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